International Journal of Evaluation and Research in Education (IJERE)
Vol. 13, No. 6, December 2024, pp. 4115~4124
ISSN: 2252-8822, DOI: 10.11591/ijere.v13i6.28395

Modelling computational thinking with game-based learning among primary school students'

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Article Info

Article history:

Received Aug 21, 2023
Revised Mar 29, 2024
Accepted May 7, 2024

Keywords:

Computational thinking
Game-based learning
Hierarchical component model
Partial least squares
Structural equation model

ABSTRACT

The computational thinking (CT) skills of students will be revised, increasing their future viewpoint in the sphere of scientific activities, notably in education interest. Game-based learning (GBL) appears to have the potential to improve students' motivation to learn. Students' GBL is associated with higher mathematics performance, and GBL's strong relationship with CT may have an even larger effect. The entirety of this CT education research is focused on undergraduate classrooms; little is revealed about how GBL support CT in K-12, particularly in primary schools. This study utilized a Structural Equation Model (SEM) in modelling the relationship between CT and GBL among primary school students. A sample of 90 primary school students from Malaysia was chosen. In this study, the Partial Least Squares-Structural Equation Model (PLS-SEM) was employed to develop the model. The results demonstrate that empirical evidence, coupled with prior observations verified the model developed. The developed model successfully confirmed all the indicator variables stated in the constructs as all of the associations within the model were significant. In conclusion, the lower order components (LOC) along with the hierarchical component model (HCM) in PLS-SEM depicted the relationship between CT and GBL, substantiated empirically.

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1. INTRODUCTION

Computational thinking (CT) is now a key component of education in the cutting-edge educational system. It is especially important to obtain a thorough grasp of student' CT skills from many viewpoints as the endeavor to incorporate CT in primary education grows [1]. Many scholars perceive CT as a collection of skills separate from those required for computer interaction or programming tasks. This requires students to acquire both domain-driven understanding as well as the ability to solve problems [2]. Chen *et al.* [3] identified the prominence of CT growth in K-12 education as an issue that was conversed the most through a clustering analysis of collected terms. Additionally, Durak and Saritepeci study [4] found that thinking styles, academic performance in mathematics, and attitudes toward mathematics were highly predictive of CT proficiency.

Computational thinking encompasses problem-solving strategies and a spectrum of cognitive abilities that surpass mere programming, applicable across various fields and domains [5]. The core components of CT

including problem formulation, decomposition, pattern discernment, algorithmic design and generalization. In today's data-driven and technologically advanced world, CT is a crucial skill set for everyone who needs to solve complicated problems or make judgments. It is not just for computer scientists or programmers. It can be developed by practice and application in diverse problem-solving scenarios and is useful in a wide range of domains, including science, engineering, business, social sciences, and everyday life [6]. The abilities cultivated by CT are highly transferable and valuable across diverse settings, encompassing logical reasoning, critical thinking, creativity and systematic problem solving.

A teaching strategy known as game-based learning (GBL) makes use of games as a pedagogical tool to encourage learning and engagement among students. As stated by Khaldi *et al.* [7], a range of game formats utilized on computers or mobile devices can serve as educational tools. These games can be made to teach specific subjects, like arithmetic, science, history, or a foreign language, or they can be made to improve more general abilities, like problem-solving, critical thinking, teamwork, and decision-making. GBL motivates students to actively engage, explore, and persist in problem solving by harnessing their enthusiasm [8]. GBL promotes active learning, in which students actively contribute to their education rather than merely absorbing it. Games offer quick, relevant feedback that can assist students in analyzing their performance, correcting their errors, and developing new abilities. Numerous advantages of GBL have been demonstrated, including enhanced learning outcomes, greater motivation and engagement, improved problem solving and critical thinking abilities, and growth in social skills like cooperation and communication [9]. It can be implemented across a range of educational environments, spanning formal classrooms to informal learning setups, and can be tailored to suit diverse age groups, subjects, and learner demographics.

The principles of CT and GBL may be blended to produce interesting educational experiences. In order to address difficult issues, CT involves breaking things down into smaller, more manageable stages and applying logic and algorithmic thinking. On the other hand, GBL entails using games as a teaching and learning method in which students participate in immersive and interactive experiences to learn new information and skills. CT can be incorporated into GBL in several ways. In problem-solving context, games provide students a rich framework in which to employ CT techniques while addressing problems. It frequently involve challenges, puzzles, and missions that demand players to exercise critical thinking, situational analysis, and strategy development. Playing games is a fun and engaging technique for students to improve their problem-solving abilities. Creating rules, mechanisms, and interactions that control how the game world behaves is a key component of algorithmic thinking in game design. This demands algorithmic thinking since game designers must establish the order and logic of the activity.

By planning, creating, and testing various game elements such as characters, objects, and actions, learners can practice algorithmic thinking [10]. According to Greipl *et al.* [11], play is the cornerstone of any game. Obviously, playing is a common occurrence in a child's development and often has a number of positive developmental consequences. One may contend that playing a game with others (e.g., in competition or cooperation) creates a unique setting that stimulates and motivates not just for winning the game or challenge but frequently for improving one's competence or skill. Moreover, there is evidence indicating that GBL confers benefits over conventional teaching methods in fostering deep learning [12]. When compared to the conventional approach, neither of the GBL strategies involving parents or not has much enhanced the children' CT in educational circumstances [13]. The outcomes also demonstrated that, in comparison to the other two strategies, the incorporation of parental involvement in the GBL approach significantly enhanced students' receptiveness towards acquiring CT. CT and GBL are closely related since both concepts require problem-solving, critical thinking, and logical reasoning abilities [14]. GBL denotes the utilization of educational games as a pedagogical strategy to enhance learning and stimulate engagement among learners.

On the contrary, CT entails a problem-solving methodology where intricate problems are deconstructed into more manageable steps, and logical, algorithmic thinking is employed to resolve them. GBL and CT place a strong emphasis on the improvement of problem-solving abilities [15]. In GBL, students encounter obstacles or issues that force them to use their critical thinking skills, situational analysis, and problem-solving abilities. Similar to analytical thinking, CT concentrates on formulating issues, designing algorithms, and using logic to solve complicated problems. Both concepts inspire students to tackle challenges methodically and strategically and provide with creative solutions. Similar to this, in GBL, players frequently need to adhere to certain guidelines, protocols, or algorithms in order to accomplish their objectives. This might entail developing strategies, making choices depending on the facts at hand, and carrying out tasks in a sequential order. Through engaging and interactive games, GBL gives students the chance to practice and improve their algorithmic thinking abilities. Both GBL and CT foster critical thinking abilities. Students must analyze events, evaluate actions, and accomplish well-informed conclusions in order to advance in GBL. Applying critical thinking abilities like analyzing data, making logical arguments, and solving problems is required for this. Similar to this, CT requires using critical thinking abilities while formulating problems, designing algorithms, and assessing the efficacy of solutions. Yadav and Oyelere [16] revealed that playing

games while studying could provide students a fun setting in which to practice and refine their critical thinking abilities. Collaborative and teamwork activities are prominent in GBL, as students get together to accomplish a task or resolve an issue. This promotes teamwork, communication, and collaboration among students as they work towards a common goal. Similarly to this, CT can entail group problem-solving, where students emerge with algorithms, analyze issues, and assess solutions. In real-world situations where teamwork and collaboration are valued, CT and GBL both foster collaborative abilities. The ability of GBL to inspire and engage students is well established. The immersive and engaging learning experiences that may be offered by well-designed educational games has the potential to boost students' desire to engage fully in the learning process. Similarly, CT also incorporates practical problem-solving and inspires learners to think critically and creatively.

The majority of the CT activities included in the study were GBL, cooperative learning, problem-based learning, and project-based learning [17]. It was found in a study by Ubaidullah *et al.* [18] that lacking highly developed CT practices could result in individuals encountering major issues that might undermine their educational or career aspirations. As the result of the educational benefits that CT offer to both instructors and students, there has been extensive implementation of teaching strategies like project-based learning and CT corresponding problem-solving procedures [19]. Numerous research probing at the relationship between CT and GBL have been performed. Digital games used in CT education have favorable impacts, but such results strongly rely on the environment in which learning is being put into practice and the users who are utilizing the games [20]. It should be emphasized that the favorable impact of GBL on students' CT implies, in a practical sense, that educators think about ways to support instructors in incorporating GBL into their classes so that students may learn more CT. It is essential to create a model that takes into consideration the relationship between GBL and CT based on the information found in this literature.

CT can be employed in a variety of disciplines and grade levels, which presents both potential and challenges. Engagement between educators and researchers from many fields and educational backgrounds is encouraged so that CT may be assessed and promoted. Hence, this study seeks to model the relationship between CT and GBL among primary school students' by utilizing SEM. The study explores theoretical underpinnings on students' CT and GBL in attempt to estimate the relationship amidst CT and GBL through SEM. The notion of learning through gaming elucidates how students acquire computational thinking concepts while actively participating in a game and accomplishing its designated objectives [21]. Students may explore CT concepts including problem-solving, decomposition, abstraction, and pattern identification when learning through games and to enhance CT skills, establishing entertaining gaming is essential [14]. In this study, a SEM for the relationship between CT and GBL among primary school students' is established and examined.

2. METHOD

The study population consisted of eleven-year-old Malaysian primary school students. Following this, the sample was chosen using the multistage cluster sampling procedure. In the first stage, the researchers randomly select a state in Malaysia from 13 states. A state selected consisted of 13 districts. In a second stage, a district was randomly selected which consisted of 11 localities/cities. In a third stage, a locality/city was then randomly selected which consisted of 12 areas. In a fourth stage, an area was randomly selected which consisted of five primary schools. At the final stage, a primary school was then randomly selected and the entire standard 5 (11 years of age) students were selected as a sample for the study. The number of students selected was 90 which comprises of three classes with the estimate of the population proportion of 0.177 and bound of error of 0.012. The general guideline suggests, as proposed by Hair *et al.* [22], which the smallest sample size allowed for a PLS-SEM model ought to be ten times the number of independent variables, taking into account both measurement and structural models, or ten times the highest count of inner model paths leading to a specific construct within the inner model. Less than nine variables are involved in the most intricate regression in this study. Moreover, as noted by Hair *et al.* [22], the entire intricacy of a structural model has minimal impact on PLS-SEM sample size requirement. This is justified by the fact that not all relationships within the structural model are computed concurrently by the PLS-SEM procedure.

A GBL module incorporated with the CT was developed and implemented in the activities of teaching and learning. The module developed consisted of the topics of fraction for primary school in Malaysia. In assessing the students' acceptance on the module development, the study utilized technology acceptance model (TAM). This study assessed students' CT by utilizing the Korkmaz CT scales survey instrument [23]. The CT scales survey instrument consisted of eight items to assess creativity, six items to assess algorithmic thinking, five items to assess critical thinking and six items to assess students' problem-solving. For this study, the adaptation of the CT scale survey instrument underwent further validation by seven panels of experts specializing in computational thinking, mathematics, and education. The research utilized the content validity index to validate CT scale survey instrument in which I-CVI for item validity and S-CVI for each and every item on the scale. The computed I-CVI ranged from 0.7143 to 1.000, and S-CVI was recorded as 0.8971, shows the allowed level of validity [24]. Moreover, Krippendorff's Alpha (KA) reliability measure was utilized to

evaluate the inter-rater reliability among the panel of experts. The obtained KA value was 0.8136, indicating that the CT instrument scales yielded precise measurements [25].

Meanwhile, TAM instrument was used to assess GBL module developed. TAM instrument consisted of 20 items where five items were regards to perceived usefulness, six items were about perceived ease of use, six items were to assess students' attitude and four items were about behavioral intention to use. TAM instrument used was validated by seven panels of experts in the field of mathematics and mathematics education. The established I-CVI were between 0.7143 and 1.000, and the S-CVI had a value of 0.8857. This shows that the TAM instrument used has the sufficient content validity [24]. Additionally, the KA inter-rater reliability among the panels of experts for the TAM instrument was recorded as 0.7988. This indicates that the TAM instrument produced measurements that were accurate [25]. The latent variables and indicator variables derived from the survey instruments with its description were depicted in Table 1.

Following the culmination of data gathering, the response data was evaluated using the SmartPLS. The research utilized a two-stage disjoint approach employing PLS-SEM reflective-reflective hierarchical component model (HCM) to evaluate the relationship between CT and GBL. The initial PLS-SEM portrayal as a research framework is depicted in Figure 1. As represented in Figure 1, the reflective-reflective HCM are CT and GBL. The lower order components (LOC) for HCM CT are algorithmic thinking, critical thinking, creativity, problem-solving and cooperativity. While the LOC for HCM GBL are attitude, behavioral intention, perceived usefulness, and perceived ease of use. The study's hypothesis examines the significant relationship among CT and GBL.

Table 1. Description of latent and indicator variables

Latent variable (construct)	Indicator variable	Description
Creativity (COY)	COY1, COY2, COY3, COY4, COY5, COY6, COY7, COY8	Creativity: The act of portraying and utilizing thoughts and ideas.
Algorithmic thinking (AO)	AO1, AO2, AO3, AO4, AO5, AO6	Algorithmic thinking: Encompasses the capacity to understand, employ, assess, and devise algorithms.
Critical thinking (CG)	CG1, CG2, CG3, CG4, CG5	Critical thinking: The utilization of cognitive abilities or methods to increase the probability of expected outcomes.
Problem-solving (PM)	PM1, PM2, PM3, PM4, PM5, PM6	Problem-solving: In the realm of education, this is acknowledged as the process of identifying a numerical problem based on specific values and determining its solution.
Cooperativity (COO)	COO1, COO2, COO3, COO4	Cooperative learning: A teaching method known as cooperative learning endeavors to improve the learning results for both individual students and groups in small-group environments.
Perceived usefulness (UF)	UF1, UF2, UF3, UF4, UF5	Perceived usefulness: Perception of oneself on performance and efficiency of a technology.
Perceived ease of use (EF)	EF1, EF2, EF3, EF4, EF5, EF6	Perceived ease of use: Perception of oneself on the easiness of features of a technology.
Attitude (AD)	AD1, AD2, AD3, AD4, AD5	Attitude: Students' attitudes are their assessments of whether using the technology will be advantageous to them.
Behavioral intention (BE)	BE1, BE2, BE3, BE4	Behavioral intention: The term behavioral intention describes how someone intends to use technology for learning both now and in the future.

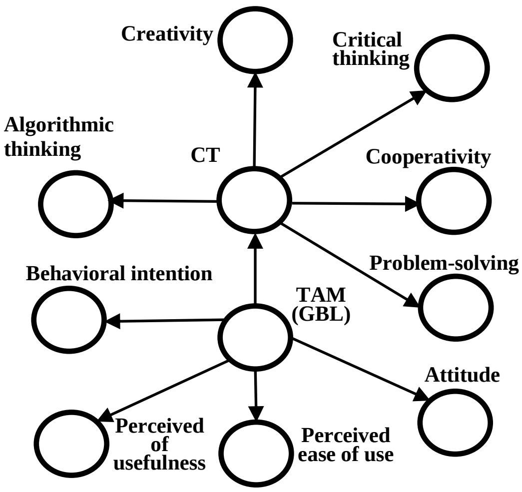

Figure 1. Framework of the study

3. RESULTS AND DISCUSSION

3.1. Structural and measurement model

The study's model is composed of two primary parts: the outer model, also referred to as the structural model, and the measurement model, which also incorporates the reflective-reflective HCM. The comprehensive model encompasses two reflective-reflective HCMs and nine measurement models, each represented by its latent and indicator variables. For CT reflective-reflective HCM, comprises of LOC, namely algorithmic thinking, critical thinking, creativity, problem-solving and cooperativity. The measurement model algorithmic thinking consisted of the indicator variables AO1, AO2, AO3, AO4, AO5 and AO6. The indicator variables CG1, CG2, CG3, CG4 and CG5 were composed in critical thinking. COY1, COY2, COY3, COY4, COY5, COY6, COY7 and COY8 were the indicator variables for creativity. The indicator variables PM1, PM2, PM3, PM4, PM5 and PM6 were composed in problem-solving. While the indicator variables COO1, COO2, COO3 and COO4 were composed in cooperativity.

The second reflective-reflective HCM was GBL consisted of four lower component models, namely attitude, behavioral intention, perceived usefulness and perceived ease of use. The indicator variables for attitude were AD1, AD2, AD3, AD4 and AD5. The indicator variables for behavioral intention were BE1, BE2, BE3 and BE4. The indicator variables for perceived usefulness were UF1, UF2, UF3, UF4 and UF5. While the indicator variables for perceived ease of use were EF1, EF2, EF3, EF4, EF5 and EF6. The path diagram connecting CT and GBL constitutes the study structural model. The reflective-reflective HCM, measurement models and structural model with its components loading and coefficient of determination were depicted in Figure 2. All indicator variables' component loadings for their respective latent variables are greater than 0.700, indicating that each indicator variable sufficiently reflects its latent variable [26].

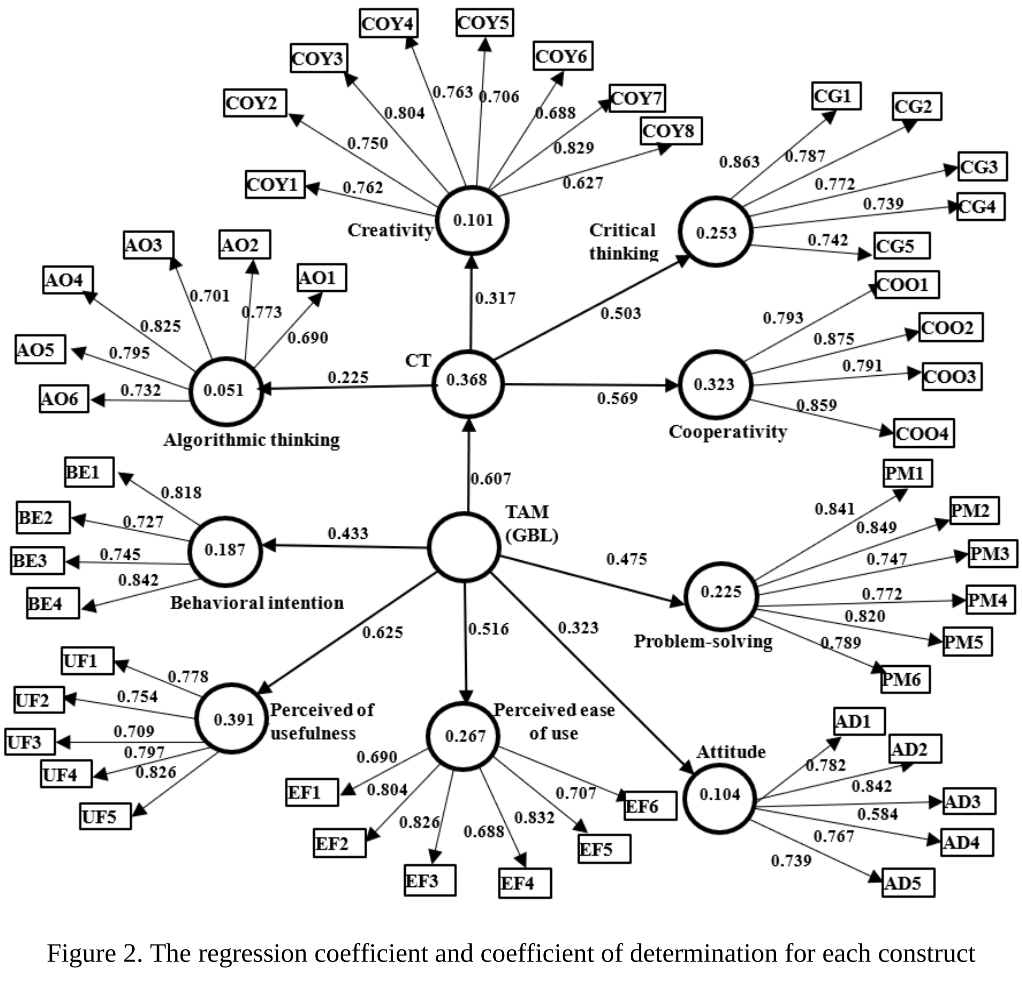

Figure 2. The regression coefficient and coefficient of determination for each construct

3.2. Measurement model validity and reliability

This section examined the constructs' validity and reliability in addition to evaluating each measurement model. When assessing the measurement model, various evaluations should be considered,

including the AVE for convergent validity, the HTMT for discriminant validity, Cronbach's alpha (α) and composite reliability for internal consistency, and outer loading for indicator reliability. A HTMT value below 0.900 indicates the establishment of discriminant validity between two reflective constructs. While the AVE higher than 0.500, Cronbach's alpha (α) and composite reliability value between 0.70 and 0.95, the convergent validity and reliability respectively are established [22]. Table 2 displays the validity, internal consistency and reliability statistics from the PLS-SEM. The values of AVE for algorithmic thinking, critical thinking, creativity, problem-solving, cooperativity, attitude, behavioral intention, perceived usefulness and perceived ease of use are greater than 0.500. This demonstrates the establishment of convergent validity, wherein all indicator variables in the model converge to represent the underlying constructs developed, as recommended by Hair *et al.* [22]. In addition, the fact that all of the constructs in Table 3 had HTMT values less than 0.850, which imply discriminant validity, have their own distinct identities and are unrelated to any other constructs in the study. As for internal consistency and reliability, all the Cronbach's alpha (α) and composite reliability value, namely AO, CG, COY, PM, COO, AD, BE, UF, and EF are higher than 0.700. This indicates that each model's indicator variable represents the related constructs.

Table 2. The reliability value of the constructs' indicator variables

Construct	Indicator variable	Indicator reliability	Composite reliability	Cronbach's alpha	AVE
Creativity	COY1	0.762	0.888	0.899	0.553
	COY2	0.750			
	COY3	0.804			
	COY4	0.763			
	COY5	0.706			
	COY6	0.688			
	COY7	0.829			
	COY8	0.627			
Algorithmic thinking	AO1	0.690	0.851	0.862	0.569
	AO2	0.773			
	AO3	0.701			
	AO4	0.825			
	AO5	0.795			
	AO6	0.732			
Critical thinking	CG1	0.863	0.841	0.856	0.611
	CG2	0.787			
	CG3	0.772			
	CG4	0.739			
	CG5	0.742			
Problem-solving	PM1	0.784	0.892	0.911	0.646
	PM2	0.857			
	PM3	0.768			
	PM4	0.768			
	PM5	0.826			
	PM6	0.780			
Cooperativity	COO1	0.793	0.849	0.854	0.689
	COO2	0.875			
	COO3	0.791			
	COO4	0.859			
Perceived usefulness	UF1	0.778	0.832	0.838	0.599
	UF2	0.754			
	UF3	0.709			
	UF4	0.797			
	UF5	0.826			
Perceived ease of use	EF1	0.690	0.853	0.869	0.579
	EF2	0.804			
	EF3	0.826			
	EF4	0.688			
	EF5	0.832			
	EF6	0.707			
Attitude	AD1	0.782	0.805	0.885	0.560
	AD2	0.842			
	AD3	0.584			
	AD4	0.767			
	AD5	0.739			
Behavioral intention	BE1	0.818	0.793	0.812	0.615
	BE2	0.727			
	BE3	0.745			
	BE4	0.842			

Table 3. The HTMT value of the model constructs

Construct	AO	AD	BE	CT	COO	COY	CG	UF	EF	PM
AD	0.480									
BE	0.426	0.633								
CT	0.533	0.371	0.276							
COO	0.220	0.214	0.268	0.594						
COY	0.445	0.345	0.382	0.482	0.199					
CG	0.464	0.474	0.440	0.769	0.202	0.426				
UF	0.359	0.438	0.589	0.196	0.392	0.235	0.282			
EF	0.173	0.265	0.290	0.538	0.759	0.210	0.216	0.548		
PM	0.288	0.310	0.245	0.722	0.351	0.171	0.575	0.136	0.328	
TAM (GBL)	0.226	0.440	0.610	0.345	0.672	0.232	0.136	0.698	0.829	0.246

Note: CT=Computational thinking, TAM (GBL)=TAM (Game-based learning)

3.3. Structural model evaluation

Structural models are evaluated by assessing the values of the formulated hypothesis path coefficients as there is a relationship between CT and GBL. A PLS-SEM bootstrap procedure was conducted, utilizing the *t*-score to evaluate the significance level of relationships. The findings indicated a significant relationship between CT and GBL (r=0.607, t=7.165, p<0.001). The resulting R^2 value, which is 0.370, indicates that 37 percent of the variance in CT can be impacted by GBL, or in other word, GBL contributed almost 37 percent to CT. The study does not distinguish from the work of Ma *et al.* [27], which shown that GB significantly improved students' CT on the whole. Furthermore, a substantial relationship among all LOC, namely algorithmic thinking, critical thinking, creativity, problem-solving and cooperativity with the HCM CT as indicated by their component loadings depicted in Figure 2. The research organized by Ponce *et al.* [26] indicate that algorithmic thinking, as a CT component, demonstrates a similar correlation pattern to our study (r=0.225, t=2.166, p<0.05). Study by Lemay *et al.* [28] found that critical thinking, as a CT constituent, does not significantly differ from our findings, which exhibit a significant relationship between CT and critical thinking (r=0.503, t=5.459, p<0.001). The study unveiled that creativity, as an integral part of CT, exhibits a significant relationship (r=0.317, t=3.135, p<0.005), consistent with Durak and Saritepeci [4]. Additionally, our study highlights the relationship between CT and problem-solving (r=0.475, t=5.064, p<0.001), as initially observed by Palts and Pedaste [29]. Moreover, the study underscores a significant relationship between cooperativity and CT (r=0.569, t=6.491, p<0.001), in-line with Durak and Saritepeci [4] research.

In the context of TAM for GBL, the study unveiled relationships throughout attitude, behavioral intention, perceived usefulness, and perceived ease of use with HCM GBL. Yeo *et al.* [30] found a positive and significant relationship between attitude towards game use and intention to use digital games, which aligns with our study where GBL statistically relates to attitude (r=0.323, t=3.202, p<0.005). The study also identified that behavioral intention is influenced by GBL, establishing a significant relationship between these constructs (r=0.433, t=4.367, p<0.001), which corresponds with Razami and Ibrahim's investigation [31] on the impact of gamification on behavioral intention. Moreover, the study found that GBL and perceived usefulness have a significant relationship (r=0.625, t=7.511, p<0.001), consistent with Krath *et al.* [32] emphasis on GBL's role in enhancing knowledge acquisition through perceived usefulness. Finally, the study demonstrated that GBL significantly contributes to students' perception of ease of use (r=0.516, t=5.651, p<0.001), mirroring research by Musyaffi *et al.* [33] on gamification quality and perceived ease of use relationship.

Research by Theodoropoulos [34] revealed that students can improve problem-solving and critical thinking through debugging games, where they identify and fix issues like bugs and errors. Debugging and troubleshooting are essential CT skills. Computational creativity, using computational tools for original solutions, can be fostered through GBL [35]. Students can create games, simulations, or interactive stories using game engines or coding platforms to express creativity and apply CT. Game data collection and analysis typically involve player behavior, game performance, or user feedback [36]. As they base decisions on gathered data, this allows students to practice data analysis and decision-making. Learners strengthen analytical and critical thinking through gaming data analysis, and learn to make data-driven decisions. Both CT and GBL can boost learners' motivation and involvement, positively impacting results. With a shared focus on cooperation, problem-solving, critical thinking, and algorithmic reasoning, CT and GBL are closely linked. CT enhances problem-solving and critical thinking, beneficial in GBL scenarios, while GBL provides an environment to develop these skills.

In the perspective of SEM, the study demonstrated practical contribution in understanding the relationship between GBL and CT by employing HCM PLS-SEM. Current research practices primarily emphasize a model that examines only the LOC of CT. Several studies [4], [28], [37] have concentrated on these LOC to analyze the relationship between CT and its constituent elements. Similarly, research by Alt [8] has examined the constituent elements of GBL using similar LOC. This study signifies a pioneering initiative

in employing HCM PLS-SEM modeling, particularly in the spheres of GBL and CT, which are recognized as vital elements in educational settings.

4. CONCLUSION

The model was adeptly developed and tested. PLS-SEM was utilized in the study to effectively validate all indicator variables, and the findings demonstrate that the developed model was strengthened by empirical evidence, aligning with previous results and the theoretical framework. The findings reveal that students' CT and GBL relationship are statistically significant. The developed HCM has made a significant contribution to the research methodology. The HCM methodological contribution is rooted in the framework it provides for comprehending and examining processes of CT and GBL. The HCM enables researchers to decomposed complex CT processes into smaller, more digestible components. This decomposition provides a pulverized analysis of CT and GBL operations, which makes it possible to examine and comprehend how various operations interact and contribute to overall performance. In conclusion, the practical contributions of CT and GBL in education can be amalgamated to create impactful educational encounters nurturing creativity, critical thinking and problem-solving skills. Beyond gaining expertise in a certain field pertaining to game content, learners can cultivate CT abilities through enjoyable and interactive gameplay, leveraging the captivating and immersive aspects of games. To the best of our understanding, this is the first study to employ the HCM with a PLS-SEM in examining the relationship between CT and GBL. The study is exploratory in design due to small sample size, which favors PLS-SEM over SEM-AMOS. The model's development can be accelerated by conducting further analysis on larger data sets.

ACKNOWLEDGEMENTS

The authors would like to express gratitude towards Sultan Idris Education University, Malaysia, and the Malaysian Ministry of Higher Education for supporting this work financially, which was made possible by grant number 2020-0045-107-01.

REFERENCES

[1] Y.-C. Liu, T.-H. Huang, and C.-L. Sung, "The determinants of impact of personal traits on computational thinking with programming instruction," *Interactive Learning Environments*, vol. 31, no. 8, pp. 4835–4849, Nov. 2023, doi: 10.1080/10494820.2021.1983610.

[2] X. Tang, Y. Yin, Q. Lin, R. Hadad, and X. Zhai, "Assessing computational thinking: A systematic review of empirical studies," *Computers & Education*, vol. 148, Apr. 2020, doi: 10.1016/j.compedu.2019.103798.

[3] H. E. Chen, D. Sun, T.-C. Hsu, Y. Yang, and J. Sun, "Visualising trends in computational thinking research from 2012 to 2021: A bibliometric analysis," *Thinking Skills and Creativity*, vol. 47, Mar. 2023, doi: 10.1016/j.tsc.2022.101224.

[4] H. Y. Durak and M. Saritepeci, "Analysis of the relation between computational thinking skills and various variables with the structural equation model," *Computers & Education*, vol. 116, pp. 191–202, Jan. 2018, doi: 10.1016/j.compedu.2017.09.004.

[5] K.-D. Boom, M. Bower, J. Siemon, and A. Arguel, "Relationships between computational thinking and the quality of computer programs," *Education and Information Technologies*, vol. 27, no. 6, pp. 8289–8310, Jul. 2022, doi: 10.1007/s10639-022-10921-z.

[6] C. Lu, R. Macdonald, B. Odell, V. Kokhan, C. Demmans Epp, and M. Cutumisu, "A scoping review of computational thinking assessments in higher education," *Journal of Computing in Higher Education*, vol. 34, no. 2, pp. 416–461, Aug. 2022, doi: 10.1007/s12528-021-09305-y.

[7] A. Khaldi, R. Bouzidi, and F. Nader, "Gamification of e-learning in higher education: a systematic literature review," *Smart Learning Environments*, vol. 10, no. 1, Jan. 2023, doi: 10.1186/s40561-023-00227-z.

[8] D. Alt, "Assessing the benefits of gamification in mathematics for student gameful experience and gaming motivation," *Computers & Education*, vol. 200, Jul. 2023, doi: 10.1016/j.compedu.2023.104806.

[9] K. Park, B. Mott, W. Min, E. Wiebe, K. E. Boyer, and J. Lester, "Generating game levels to develop computer science competencies in game-based learning environments," in *Artificial Intelligence in Education*, 2020, pp. 240–245. doi: 10.1007/978-3-030-52240-7_44.

[10] W. Zhao and V. J. Shute, "Can playing a video game foster computational thinking skills?" *Computers & Education*, vol. 141, Nov. 2019, doi: 10.1016/j.compedu.2019.103633.

[11] S. Greipl, K. Moeller, and M. Ninaus, "Potential and limits of game-based learning," *International Journal of Technology Enhanced Learning*, vol. 12, no. 4, pp. 363–389, 2020, doi: 10.1504/IJTEL.2020.110047.

[12] F. Crocco, K. Offenholley, and C. Hernandez, "A Proof-of-Concept Study of Game-Based Learning in Higher Education," *Simulation & Gaming*, vol. 47, no. 4, pp. 403–422, Aug. 2016, doi: 10.1177/1046878116632484.

[13] X. Zhang *et al.*, "Developing rural Chinese children's computational thinking through -game-based learning and parental involvement," *The Journal of Educational Research*, vol. 116, no. 1, pp. 17–32, Jan. 2023, doi: 10.1080/00220671.2023.2167798.

[14] T. Turchi, D. Fogli, and A. Malizia, "Fostering computational thinking through collaborative game-based learning," *Multimedia Tools and Applications*, vol. 78, no. 10, pp. 13649–13673, May 2019, doi: 10.1007/s11042-019-7229-9.

[15] F. J. Agbo, S. S. Oyelere, J. Suhonen, and M. Tukiainen, "Design, development, and evaluation of a virtual reality game-based application to support computational thinking," *Educational technology research and development*, vol. 71, no. 2, pp. 505–537, Apr. 2023, doi: 10.1007/s11423-022-10161-5.

[16] A. K. Yadav and S. S. Oyelere, "Contextualized mobile game-based learning application for computing education," *Education and Information Technologies*, vol. 26, no. 3, pp. 2539–2562, May 2021, doi: 10.1007/s10639-020-10373-3.

[17] T.-C. Hsu, S.-C. Chang, and Y.-T. Hung, "How to learn and how to teach computational thinking: Suggestions based on a review of the literature," *Computers & Education*, vol. 126, pp. 296–310, Nov. 2018, doi: 10.1016/j.compedu.2018.07.004.
[18] N. H. Ubaidullah, Z. Mohamed, J. Hamid, S. Sulaiman, and R. L. Yussof, "Improving novice students' computational thinking skills by problem-solving and metacognitive techniques," *International Journal of Learning, Teaching and Educational Research*, vol. 20, no. 6, pp. 88–108, Jun. 2021, doi: 10.26803/ijlter.20.6.5.
[19] A. Saad and S. Zainudin, "A review of project-based learning (PBL) and computational thinking (CT) in teaching and learning," *Learning and Motivation*, vol. 78, May 2022, doi: 10.1016/j.lmot.2022.101802.
[20] A. Theodoropoulos and G. Lepouras, "Digital game-based learning and computational thinking in P-12 education: A systematic literature review on playing games for learning programming," in *Handbook of Research on Tools for Teaching Computational Thinking in P-12 Education*, 2020, pp. 159–183. doi: 10.4018/978-1-7998-4576-8.ch007.
[21] S. Sukirman, L. F. M. Ibharim, C. S. Said, and B. Murtiyasa, "A strategy of learning computational thinking through game based in virtual reality: Systematic review and conceptual framework," *Informatics in Education*, vol. 21, no. 1, Jun. 2021, doi: 10.15388/infedu.2022.07.
[22] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A primer on partial least squares structural equation modeling (PLS-SEM)*. SAGE Publications, 2022.
[23] Ö. Korkmaz, R. Çakir, and M. Y. Özden, "A validity and reliability study of the computational thinking scales (CTS)," *Computers in Human Behavior*, vol. 72, pp. 558–569, Jul. 2017, doi: 10.1016/j.chb.2017.01.005.
[24] M. S. B. Yusoff, "ABC of content validation and content validity index calculation," *Education in Medicine Journal*, vol. 11, no. 2, pp. 49–54, Jun. 2019, doi: 10.21315/eimj2019.11.2.6.
[25] K. Krippendorff, *Content analysis: An introduction to its methodology*. Sage Publications, 2018.
[26] B. Alfaro-Ponce, A. Patiño, and J. Sanabria-Z, "Components of computational thinking in citizen science games and its contribution to reasoning for complexity through digital game-based learning: A framework proposal," *Cogent Education*, vol. 10, no. 1, Dec. 2023, doi: 10.1080/2331186X.2023.2191751.
[27] J. Ma, Y. Zhang, Z. Zhu, S. Zhao, and Q. Wang, "Game-based learning for students' computational thinking: A meta-analysis," *Journal of Educational Computing Research*, vol. 61, no. 7, pp. 1430–1463, Dec. 2023, doi: 10.1177/07356331231178948.
[28] D. John Lemay, R. B. Basnet, T. Doleck, P. Bazelais, and A. Saxena, "Instructional interventions for computational thinking: Examining the link between computational thinking and academic performance," *Computers and Education Open*, vol. 2, Dec. 2021, doi: 10.1016/j.caeo.2021.100056.
[29] T. Palts and M. Pedaste, "A model for developing computational thinking skills," *Informatics in Education*, vol. 19, no. 1, pp. 113–128, Mar. 2020, doi: 10.15388/infedu.2020.06.
[30] S. Yeo, T. Rutherford, and T. Campbell, "Understanding elementary mathematics teachers' intention to use a digital game through the technology acceptance model," *Education and Information Technologies*, vol. 27, no. 8, pp. 11515–11536, Sep. 2022, doi: 10.1007/s10639-022-11073-w.
[31] H. Hafiza Razami and R. Ibrahim, "Models and constructs to predict students' digital educational games acceptance: A systematic literature review," *Telematics and Informatics*, vol. 73, Sep. 2022, doi: 10.1016/j.tele.2022.101874.
[32] J. Krath, L. Schürmann, and H. F. O. von Korflesch, "Revealing the theoretical basis of gamification: A systematic review and analysis of theory in research on gamification, serious games and game-based learning," *Computers in Human Behavior*, vol. 125, Dec. 2021, doi: 10.1016/j.chb.2021.106963.
[33] A. M. Musyaffi, W. A. Sulistyowati, C. W. Wolor, and A. A. Sasmi, "Game-based learning sustainability during social distance: The role of gamification quality," *European Journal of Educational Research*, vol. 11, no. 3, pp. 1289–1302, Jul. 2022, doi: 10.12973/eu-jer.11.3.1289.
[34] A. Theodoropoulos, "Participatory design and participatory debugging: Listening to students to improve computational thinking by creating games," *International Journal of Child-Computer Interaction*, vol. 34, Dec. 2022, doi: 10.1016/j.ijcci.2022.100525.
[35] D. Hooshyar, L. Malva, Y. Yang, M. Pedaste, M. Wang, and H. Lim, "An adaptive educational computer game: Effects on students' knowledge and learning attitude in computational thinking," *Computers in Human Behavior*, vol. 114, Jan. 2021, doi: 10.1016/j.chb.2020.106575.
[36] J. Tay, Y. M. Goh, S. Safiena, and H. Bound, "Designing digital game-based learning for professional upskilling: A systematic literature review," *Computers & Education*, vol. 184, Jul. 2022, doi: 10.1016/j.compedu.2022.104518.
[37] M.-J. Tsai, J.-C. Liang, S. W.-Y. Lee, and C.-Y. Hsu, "Structural validation for the developmental model of computational thinking," *Journal of Educational Computing Research*, vol. 60, no. 1, pp. 56–73, Mar. 2022, doi: 10.1177/07356331211017794.

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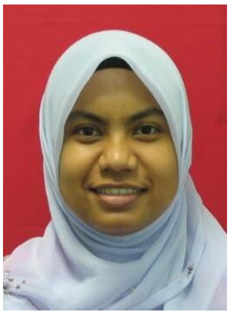

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